特集 Contextual Scene Segmentation of Driving Behavior based on Double Articulation Analyzer*

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Various advanced driver assistance systems (ADASs) have recently been developed, such as Adaptive Cruise Control and Precrash Safety System. However, most ADASs can operate in only some driving situations because of the difficulty of recognizing contextual information. For closer cooperation between a driver and vehicle, the vehicle should recognize a wider range of situations, similar to that recognized by the driver, and assist the driver with appropriate timing.
In this paper, we assumed a double articulation structure in driving behavior data and segmented driving behavior into meaningful chunks for driving scene recognition in a similar manner to natural language processing (NLP). A double articulation analyzer translated the driving behavior into meaningless *manemes*, which are the smallest units of the driving behavior just like *phonemes* in NLP, and from them it constructed *navemes*, which are meaningful chunks of driving behavior just like *morphemes*. As a result of this two-phase analysis, we found that driving chunks equivalent to language words were closer to the complicated or contextual driving scene segmentation produced by human recognition.

Key words：Driving context, Scene segmentation, Double Articulation Analyzer, Nonparametric Bayes

I. INTRODUCTION

Driving is a cooperative operation between a driver and his or her vehicle. The steering wheel and pedals convey the driver's intention to the vehicle, and the vehicle reflects the intention in its behavior. Various advanced driver assistance systems (ADASs) have recently been developed, such as Adaptive Cruise Control (ACC), the Precrash Safety System (PCS), and the Lane Keeping Assist System. These ADASs provide safe and comfortable driving by controlling the vehicle automatically: ACC controls the vehicle speed depending on the situation and PCS brakes the vehicle to minimize collision impact. Thus, the driver and the vehicle interact closely to drive in safety and comfort.

However, most ADASs can operate in only some driving situation, e.g., while cruising on a freeway and immediately before a crash. This is because the systems can recognize the current situation only in limited circumstances. For closer cooperation between the driver and vehicle, the vehicle should recognize a wider range of situations, similar to the range recognized by the driver, and assist the driver with appropriate timing. Thus, we use the contextual scene segmentation method to segment multimodal driving behavior into semantic chunks. This method will improve ADASs in terms of their ability to recognize the driving scene like the driver.

To segment driving behavior, many kinds of statistical modeling techniques have been used in previous works, such as the Hidden Markov Model (HMM)[1] and the Hybrid Dynamical System [2) 3)]. However, most of them do not consider the meaning of the segments. These models discretized the driving behavior in physical feature space directly, i.e., they extract the segments as physical segments, not as semantic segments.

In contrast, linguists analyze language as a double articulation structure, which has two layers of elements; *phonemes* and *morphemes*. A phoneme is the smallest segmental unit of sound, and a morpheme is the smallest semantically meaningful unit. In the natural language processing area, word segmentation generally needs a massive parsed corpus [4)]. For unknown words that are not included in the lexicon, unsupervised word segmentation based on a non-parametric Bayesian approach has been developed recently [5)].

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In this paper, we assume a double articulation structure in driving behavior data, i.e., the driving behavior has a hierarchy of *manemes*, which are the smallest meaningless units of time-series maneuvers, and *navemes*, which are the smallest meaningful units of the manemes (**Fig. 1-A**). The sticky Hierarchical Dirichlet Process Hidden Markov Model (sticky HDP-HMM) [6] is used to extract manemes from the driving behavior, and the Nested Pitman-Yor Language Model (NPYLM) [5] is used to construct navemes from time-series of manemes. These two nonparametric Bayesian approaches provide unsupervised semantic segmentation of multimodal continuous driving behavior. This hierarchical analyzer is called a double articulation analyzer in this paper. The analyzer determines manemes/navemes and the most likely numbers of them simultaneously in a statistically data-driven inference.

The effectiveness of the double articulation analyzer in terms of contextual scene segmentation was evaluated through the similarity between segments extracted by the double articulation analyzer and segments labeled by human subjects watching a video recording of the driving behavior. As a similarity metric, we used the well-known F-measure. We found that navemes were more similar to the driving scene label than manemes. In addition, navemes were also more similar to the direction-of-motion label; each naveme is composed of smaller behaviors: slowing down, steering, and accelerating. These results suggest that driving behavior may have a double articulation structure in common with languages.

This paper is organized as follows. The sticky HDP-HMM and NPYLM are outlined in section 2, the experimental setup is described in section 3, and experimental results are presented in section 4. Section 5 is discussion and section 6 concludes the paper.

II.　DOUBLE ARTICULATION ANALYZER

This section outlines the double articulation analyzer. Taniguchi et al [7) 8)]. proposed a double articulation analyzer for multimodal sensor data. They successfully extracted an articulation structure from human motion capture data by using a sticky HDP-HMM and NPYLM, assuming the double articulation structure in the motion capture data. In this paper, this analyzer is applied to a driving data. The sticky HDP-HMM and NPYLM are outlined below.

A.　Sticky HDP-HMM

First, we segmented driving behavior as continuous and multimodal time-series data (throttle opening, brake master cylinder pressure, steering angle, velocity, etc.) in physical feature space using the sticky HDP-HMM.

For time-series data discretization, an HMM has been widely used. Latent discrete variables are defined as hidden states in the HMM. The hidden state transitions from the previous hidden state through a conditional distribution and generates the corresponding observation data. In the conventional HMM, the number of hidden states is assumed to be known, but it is actually unknown in the driving behavior data. In contrast, an HMM based on a nonparametric Bayesian approach has been proposed recently [6) 9)]. The Hierarchical Dirichlet Process Hidden Markov Model (HDP-HMM) [9] can

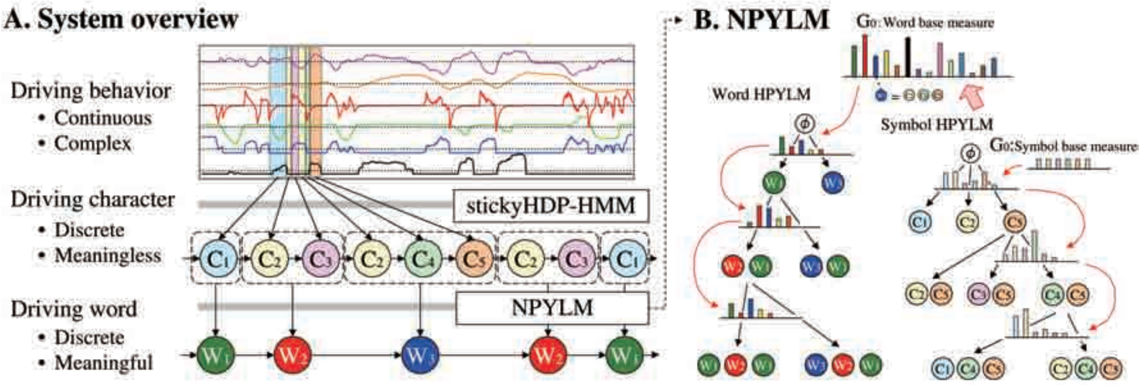

Fig. 1　(A)Overview of a double articulation analyzer. The analyzer discretizes driving behavior into manemes, which are the smallest meaningless units of driving maneuver, and from them it constructs navemes, which are the smallest meaningful units of driving maneuver. The translation into manemes is achieved by the sticky HDP-HMM, and the construction into navemes is achieved by the Nested Pitman-Yor Language Model (NPYLM). (B) Overview of NPYLM. Two n-gram models—a character n-gram and a word n-gram—are used in NPYLM to express the probabilistic distribution of any words.

estimate the number of hidden states simultaneously on the basis of a prior distribution of the number. The sticky HDP-HMM [6], which is an extension of the HDP-HMM, can reduce the frequency of transition among hidden states by biasing the self-transition probability.

In the sticky HDP-HMM, an infinite number of hidden states are assumed by an infinite-dimensional prior of the number through a nonparametric Bayesian approach. A graphical model of the sticky HDP-HMM is shown in **Fig.2**. An infinite-dimensional prior of the number of the hidden states β is generated from a stick breaking process with parameter γ. Transition probability π_k is generated from the Dirichlet process using concentration parameter α, a self-transition parameter κ, and the prior β, where k is the index of hidden states. An observation y_t is generated from the distribution of the corresponding hidden state c_k with distribution parameter θ_k, where t is the time index.

$$\beta \mid \gamma \sim \mathrm{GEM}(\gamma). \tag{1}$$
$$\pi_k \mid \alpha, \kappa, \beta \sim \mathrm{DP}\left(\alpha+\kappa, \frac{\alpha\beta+\kappa\delta_k}{\alpha+\kappa}\right). \tag{2}$$

$$c_{t+1} \mid \{\pi_k\}_{k=1}^{\infty}, c_t \sim \pi_{c_t}. \tag{3}$$
$$y_t \mid \{\theta_k\}_{k=1}^{\infty}, c_t \sim F(\theta_{c_t}). \tag{4}$$

In this paper, the driving behavior distribution is modeled as a Gaussian distribution and a blocked Gibbs sampler is used as the inference method [6].

$$\theta_k = (\mu_k, \Sigma_k) \tag{5}$$
$$y_t \mid \{\mu_k, \Sigma_k\}_{k=1}^{\infty}, c_t \sim \mathcal{N}(\mu_{c_t}, \Sigma_{c_t}) \tag{6}$$

Here, the estimated time-series of hidden states $\{c_t\}_{t=1}^{T}$ are called manemes. The manemes are discrete time-series that reflect the cluster of driving behavior in the physical feature space. They have no explicit meaning.

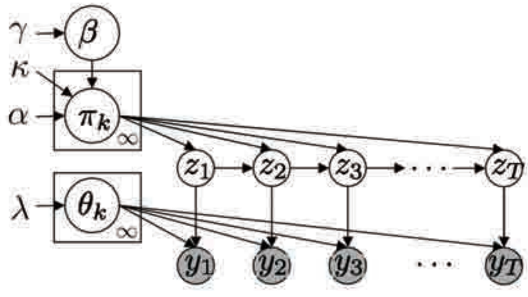

Fig. 2　Graphical model of the sticky HDP-HMM [6].

B.　Nested Pitman-Yor Language Model

Second, we chunked the time-series of manemes using an unsupervised morphological analysis in *Natural Language Processing* (NLP), i.e., the Nested Pitman-Yor Language Model (NPYLM).

In NLP, morphological analysis is the extraction of morphemes, which are the smallest semantically meaningful units in a language. In other words, morphological analysis is a segmentation of phonemes in speech or segmentation of characters in a text. Conventional morphological analyses have required a massive parsed corpus as training data for machine learning. In contrast, Mochihashi et al. proposed NPYLM, which segments characters using a massive unparsed text and a probabilistic language model instead of a massive parsed corpus.

In NPYLM, two n-gram language models form a hierarchical structure: one is a character n-gram and the other is a word n-gram. Both n-grams are described by the Hierarchical Pitman-Yor Language Model (HPYLM)[10]. HPYLM is a model for generating an infinite-dimensional n-gram distribution by using a Pitman-Yor process (PY), as a generalization of the Dirichlet process. PY is a stochastic process with discount parameter d and similarity parameter θ. It generates discrete probabilistic distribution G, which is similar to another distribution G_0, called the base measure. In HPYLM, the word n-gram distribution is generated from PY by using the word (n-1)-gram distribution.

$$\mathrm{G}_1 = \{p(\cdot)\}, \mathrm{G}_1 \sim \mathrm{PY}(\mathrm{G}_0, d, \theta). \tag{7}$$
$$\mathrm{G}_2 = \{p(\cdot \mid w_1)\}, \mathrm{G}_2 \sim \mathrm{PY}(\mathrm{G}_1, d, \theta). \tag{8}$$
$$\mathrm{G}_3 = \{p(\cdot \mid w_1 w_2)\}, \mathrm{G}_3 \sim \mathrm{PY}(\mathrm{G}_2, d, \theta). \tag{9}$$

However, in the case of unknown words not in the lexicon, the base measure G_0 of these words is not available, which leads to the generation of a unigram distribution: the occurrence probability of any words. In NPYLM, therefore, the base measure G_0 is given by means of the character n-gram model, which is also described by HPYLM. This means that NPYLM allows any words to be generated.

$$\mathrm{G}_0(w) = p(c_1 c_2 \cdots c_L) \tag{10}$$

In this paper, NPYLM is applied to time-series of manemes estimated by the sticky HDP-HMM. The word n-gram is estimated using the blocked Gibbs sampler, which resamples one sentence in each iteration instead of one word [5]. To make NPYLM applicable to driving behavior, the manemes are treated as driving characters and time-series sequences of manemes from departure to parking are treated as one driving sentence.

Here, an estimated chunk of the manemes is called a naveme. The navemes are a set of the manemes that appear repeatedly in driving behavior. Moreover, the navemes are expected to be meaningful to drivers.

III. EXPERIMENTS

To evaluate the effectiveness of the double articulation analyzer, we segmented multimodal driving behavior data observed in a real car into manemes and navemes and compared them with the segments labeled by human subjects.

A. Experimental Paradigm

In the experiment, a subject drove a real car along the two courses shown in **Fig. 3**, five times per course, and the driving data were recorded. Each drive started in the resting state before departure and finished in the resting state after parking at the same position. Recorded driving data were throttle opening, brake master cylinder pressure, steering angle, and vehicle velocity. The sampling rate for recording was 10 frame per second (fps).

Photographs taken during the experiment by a camera mounted on the car are shown in **Fig. 4**.

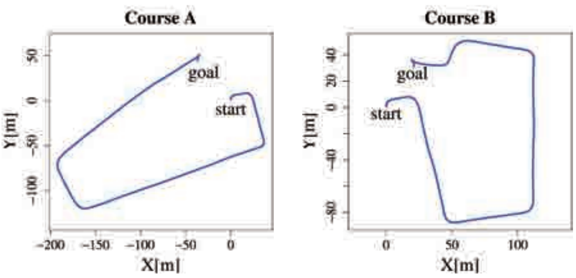

Fig. 3　Two driving courses used in the experiment. The vehicle trajectories were estimated from odometry data. Therefore, the positions deviated from the true data, e.g., the start and goal were actually the same position whereas they are different in the figure.

Fig. 4　Typical images of the driving scene. The driver drove a short course in only about two minutes; the course included some pedestrians and other vehicles.

B. Preprocessing

In a preprocessing step, the differential values of steering angle and vehicle velocity were calculated as dynamic features. All the observed data (throttle opening, brake master cylinder pressure, steering angle, and vehicle velocity) and these two dynamic features were normalized into standard scores with a mean of zero and variance of one. Finally, these six-dimensional data were used as observed driving behavior.

C. Learning of manemes and navemes

First, the sticky HDP-HMM was trained with all the driving behaviors for the 10 drives. The number of iterations for the blocked Gibbs sampler was set to 100, and the maximal number of hidden states was 60; both of these are the implementation parameters for the sticky HDP-HMM. The adequacy of these parameters was confirmed in a preliminary experiment.

After the sticky HDP-HMM's training, 100 time-series of manemes for each of the 10 drives were sampled for navemes learning and evaluation. Each maneme time-series is called a sentence. In this way, 1000 sentences of manemes were sampled by the trained sticky HDP-HMM.

Second, the NPYLM was trained with all of 1000 sentences of manemes. The number of iterations of the blocked Gibbs sampler was set to 100,000, the maximal character length of words was 8, and n-gram word model was set to bigram.

After the NPYLM's training, 10 time-series of navemes for each of the 1000 sentences of manemes were sampled for evaluation. In this way, 10,000 sentences of navemes were sampled by the trained NPYLM.

D. Evaluation

To evaluate the similarity between manemes/navemes and human recognition of driving scenes, we focused on the segmentation points of manemes and navemes.

We asked three human subjects to segment a driving video into chunks of corresponding to the four labeling-terms shown in **Table 1**. The running state, vehicle direction, and surrounding circumstances are examples of physical terms. In contrast, the driving scene is an example of contextual recognition by a human. We instructed the subjects to segment only according to these labeling-terms, so they had discretion in deciding the details of labels, i.e., stop, go, accelerate, and slow down, etc.

Segmentation points estimated by the double articulation analyzer (analyzer points) were compared with those by human subjects (human points) via the F-measure, which is harmonic mean of precision and recall, to evaluate the similarity between them. The analyzer estimated analyzer points 100 times from the driving data for each drive, so the F-measure was calculated 100 times for each analyzer points of manemes and navemes across the subjects and across the labeling-terms. In the F-measure calculation, precision was calculated as the ratio of the number of analyzer points corresponding to human points and all analyzer points, and recall was calculated as the ratio of the number of analyzer points corresponding to human points and all human points. Note that "A corresponding to B" means that the time delay between A and the nearest point in B is shorter than 2.5[s].

Table 1　LABELING TERMS AND EXAMPLES OF LABELS

Labeling term	Label example
running state	stop, go, accelerate, decelerate, ...
vehicle direction	forward/backward, left/right, ...
surrounding circumstances	other vehicles, pedestrians, ...
driving scene	turn, parking, wait for pedestrian on crossing, ...

IV. RESULTS

A. Result overview

The results of the analysis of driving data for course B are overviewed in **Fig. 5**. The upper figure shows the occurrence probability of segmentation points of manemes and the middle figure shows the occurrence probability of segmentation points of navemes. These probabilities were calculated by performing 100-times sampling repeatedly. The lower figure shows the segmentation points of the three human subjects.

The results show that the navemes were significantly organized, while the manemes were often fine segmented. Human segmentation points were not much different. Moreover, there were many maneme segmentation points around the naveme segmentation points. These were consistent trends across the courses and each drives.

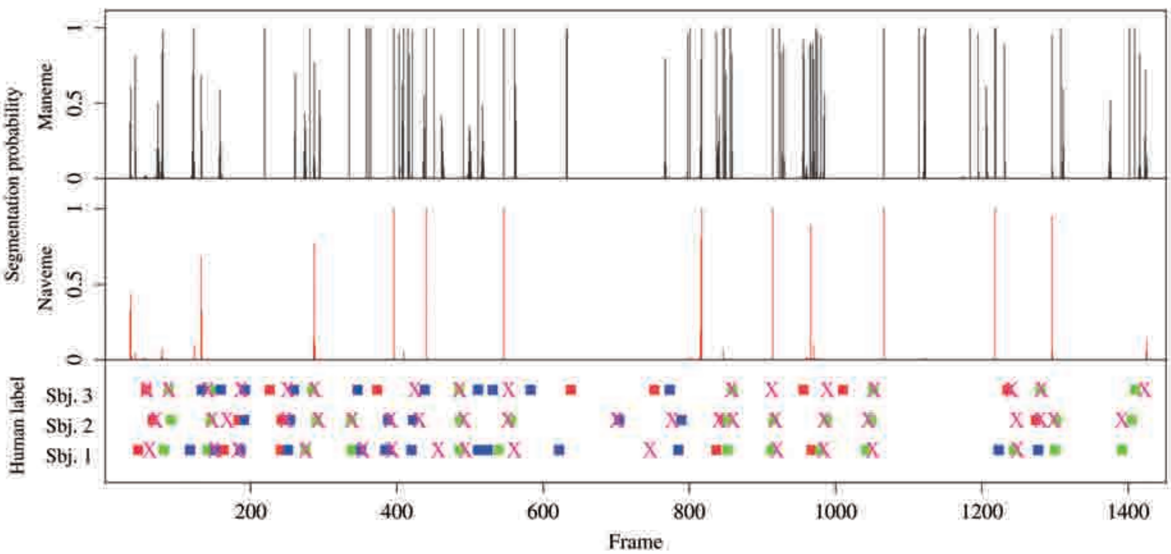

Fig. 5　Overview of results of maneme/naveme segmentation and human segmentation points. The upper figure shows the maneme segmentation probability and the middle figure shows the naveme segmentation probability. The lower figure shows the human segmentation points. Red marks indicate the points related to running state, green marks indicate ones related to vehicle direction, blue marks indicate the points related to the surrounding circumstances, and pink marks indicate points where the humans felt the scene switched.

B. Lengths of manemes/navemes

Histograms of the lengths of manemes and navemes are shown in **Fig. 6**. The left figure shows the maneme length and the center figure shows the naveme length in the data sampling frame. They show the effectiveness of chunking from manemes to navemes by NPYLM, i.e., navemes are significantly longer than manemes. The right figure shows the number of manemes per naveme. The distribution has bimodality, which suggests that the navemes can be categorized into two types: long words and short words, like particles in language.

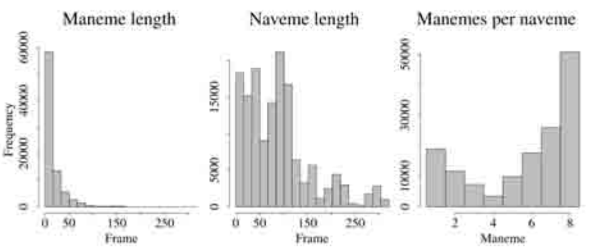

Fig. 6 Histograms of character/word length and number of characters in a word. Word length (center figure) is significantly longer than character length (left figure). The number of characters in a word has a bimodal distribution (right figure).

C. Comparison of manemes/navemes with human recognition

F-measures indicating the correspondence between manemes/navemes and human recognition are shown in **Fig. 7**. All of the bars in both the left and right figures show averages of F-measures among the three human subjects. The left and right figures show F-measures for physical and contextual labels.

For the physical labels (**Fig. 7-A**), the F-measure of navemes were respectively higher than those of manemes. Especially, the F-measures of navemes of vehicle direction was higher than the others. We think that this is because the running state label and surrounding circumstances label were directly related to simple physical quantities compared with the vehicle direction label was a complex mixture of physical quantities, such as accelerate/decelerate and left/right turn. In addition, the F-measures of both manemes and navemes for the surrounding circumstances label were lower than those of the vehicle direction label. We think that this is because the surrounding circumstances label also contained situations unrelated to driving behavior, such as far vehicles and pedestrians on the sidewalk.

On the other hand, for contextual labels (**Fig. 7-B**), the F-measure of navemes was higher than the F-measure of manemes. We think that this is because the driving scene change points recognized by humans depend on the vehicle direction and some of the surrounding circumstances related to driving behavior (**Fig. 5**).

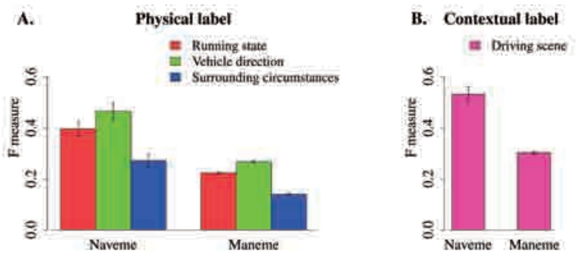

Fig. 7 F-measure evaluating the correspondence between segmentation points estimated by a double articulation analyzer and physical labels (A) and contextual labels (B) assigned by humans. Error bars indicate the standard deviation of the F-measure due to not only individual differences but also the probabilistic sampling method.

V. DISCUSSION

We analyzed the correspondence between a double articulation analyzer based on the double articulation structure of manemes and navemes in driving behavior and human recognition of the driving scene. From another different viewpoint of segmentation, the double articulation analyzer filters the maneme segmentation points by considering context, so that the filtered segmentation points divide the driving behavior into long-term chunks. This filtering is achieved by estimating the likeliest lexicon of navemes to maximize the probability of generating the provided driving data, so that complex driving behaviors are extracted as navemes, such as right/left turn, which is composed of slowing down, steering, and acceleration. Interestingly, this filtering also extracts the segmentation points that human recognize as driving scene change points.

Contextual labels are more complex than any physical labels, as shown in **Table 1**. This means that humans perceive driving scenes as vague chunks in a large sense, and these large chunks can be decomposed into small physical chunks of driving. The double articulation analyzer captures the attributes of contextual labels by assuming the double articulation structure. By assembling physical labels in the statistically likeliest combination through a nonparametric Bayesian approach, it extracts the segmentation points that well explain human driving scene recognition. It is interesting that the estimated segmentation points correspond to human recognition even though the data-driven estimation is based on only maximization of the driving behavior generative probability.

The effectiveness of the contextual scene segmentation, i.e., a symbolization framework of driving behavior based on physical and semantic perspectives has been reported on the basis that the symbolization enabled a long-term prediction of driving behavior [11]. In the present paper, we showed that the semantic symbolization is related to a human recognition of a driving scene. This suggests that driving behavior has a double or higher articulation structure in common with linguistics, where physical and semantic symbols provide a hierarchical structure.

The results of segmentation similar to human recognition are expected to lead to novel ADASs. In the future, a driver and vehicle will communicate with each other and cooperate in a real sense to drive the vehicle. This is a different approach from an automated driving system [12] that controls a vehicle without the driver performing any maneuvers. Our approach of contextual segmentation that does not require any expensive and high-performance sensors will contribute to the popularization of safer vehicles.

To achieve this contribution, we need to evaluate the effectiveness of our approach with more subjects in various driving scenes. Moreover, an investigation of symbolization from other driving modalities, such as the driver's biological signals, environmental images recorded from car-mounted cameras, and the behavior of surrounding vehicles, is also important future work.

VI. CONCLUSION

In this paper, we examined a symbolization framework based on a double articulation structure of manemes and navemes that extracted the driving context change points recognized by humans. In our experiments, navemes had higher correspondence with the human-recognized driving context than manemes. This result suggests that human recognition of driving behavior is based on a double articulation structure in driving behavior. Our contextual scene segmentation method is expected to lead to novel driver assistance systems which selects an appropriate ADAS according to a driving scene comfortably for human.

To develop and verify our method, we will apply it to a wider range of driving behavior recorded on ordinary roads by many drivers and in various different environments such as different times of day, weather, regions, and countries. Our future work will include applying it not only to driving behavior but also to other kinds of driving data, such as the driver's biological signals, environmental images recorded from car-mounted cameras, and the behavior of surrounding vehicles.

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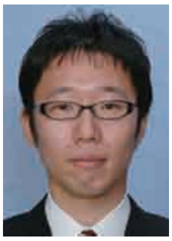

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